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Spatial analysis of China province-level CO_2 emission intensity

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ABSTRACT

This study offers a unique contribution to the literature by investigating the influential factors of energy-related, carbon dioxide emission intensity among a panel of 30 provinces in China covering the period 1991–2010. We use novel spatial panel data models to analyze the drivers of energy-related emission intensity, which we posit are characterized by spatial dependence. Our results suggest (1) emission intensities are negatively affected by per-capita, province-level GDP and population density; (2) emission intensities are positively affected by the structure of energy consumption and the transportation sector; and, (3) energy prices have no effect on emission intensities.

Contents

1. Introduction

Understanding the geographic distribution of sources of carbon dioxide emissions (CO_2) can aid policy in combating climate change. The geographic distribution of emissions does not affect the climatic impact of greenhouse gas emissions, but the distribution of economic activity and energy consumption does affect local regions which are the source of emissions. Combating global climate change will require multilateral, international agreements,

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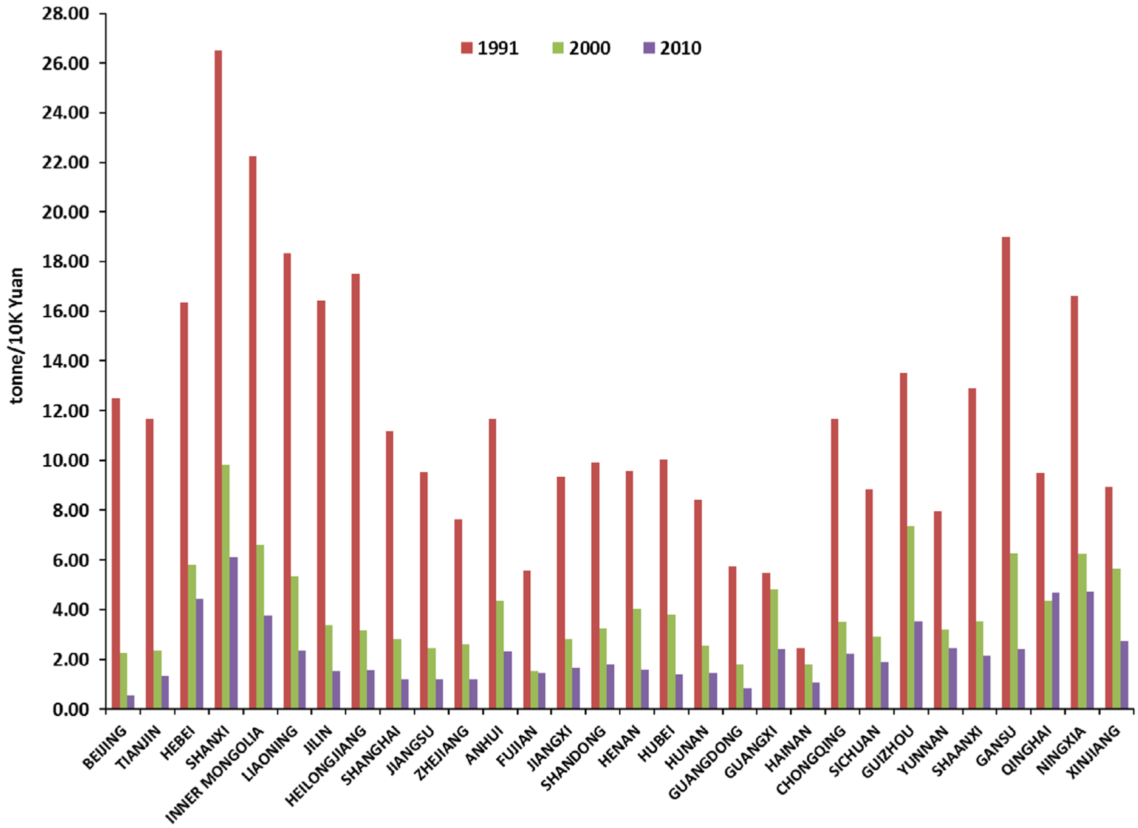

Fig. 1. Provincial CO_2 emission intensity through time.

but the fight against local climate change causes will start at home. That is, mitigation policies will likely come at the expense of economic growth among provinces in China. Spatial spillovers indicate that policies adopted in one province will affect policies in neighboring provinces, which implies that provinces may strategically interact to balance mitigation and economic policy goals. A line of research within the urban economics and regional science literature explores this type of strategic interaction among jurisdictions by explicitly modeling how one jurisdiction's policies affect neighboring policies and vice versa (see [1] for a review). We abstract away from strategic interaction models and instead focus on the proper estimation of spatial dependence among province-level CO_2 emission intensity and the economic drivers of such emissions.

Examining this relationship is important as China surpassed the US to become the largest aggregate emitter of CO_2 emissions in 2006, according to a recent report released by the Netherlands Environmental Assessment Agency.[3] Since the market-oriented reforms of 1978, China, as a whole, has experienced remarkable economic growth accompanied by a very high demand of energy consumption. From 1991 to 2010, national-level GDP increased from approximately 2,178.15 billion Chinese Yuan (CNY) to 40,120.20 billion CNY in China. This increase marks an average annual growth rate of 15.68%. During this same period, national-level energy consumption increased from 1.04 billion tons of standard coal equivalent (tce) to 3.25 billion tce. Yet, an analysis at a more disaggregated level reveals an imbalance in economic growth and energy consumption among different regions in China. For example in 2010, Jiangsu, Shandong, and Guangdong provinces accounted for over 3 trillion CNY in GDP whereas provinces such as Hainan, Qinghai, and Ningxia accounted for less than 300 billion CNY. These disparities also reveal themselves in terms of province-level CO_2 emissions.

We choose three points in time (1991, 2000, and 2010), to display China's provincial CO_2 emission intensity distribution, which are shown in Fig. 1. From 1991 to 2010, the CO_2 emission intensity of each province decreased year by year. The results show that provinces such as Shanxi and Ningxia consistently have the highest CO_2 emission intensities – their CO_2 emission intensities are almost six times higher that provinces such as Hainan and Guangdong. That means, in order to produce the same GDP, the provinces with the highest CO_2 emission intensity will produce about six times the CO_2 emissions as the provinces with the lowest CO_2 emission intensity. The disparity of CO_2 emission intensity reveals itself in trends of spatial clustering. As displayed in Fig. 2, the northern and western provinces are aggregated in terms of their higher CO_2 emission intensities, and the southern and eastern provinces are generally aggregated in terms of their low CO_2 emission intensities. Fig. 2 displays the average CO_2 emission intensities for 1991–2010.

In this study, we seek to examine the geographical distribution of the driving forces of CO_2 emission intensities in China. Our estimate of CO_2 is based upon province-level energy consumption. Therefore, these estimates represent energy-related emission intensities, but we will use the terms CO_2 emission intensity and energy-related intensity interchangeable throughout the remainder of the manuscript. This estimate of emissions is consistent with emission estimates found within such sources as the International Energy Agency, the U.S. Energy Information Administration, the British Petroleum Statistical Review of World Energy, the World Bank, and the United Nations [2–6]. The reason that these energy-related estimates are used is because it would be too costly to

[3] The report can be accessed online at: http://www.pbl.nl/en/dossiers/Climatechange/moreinfo/Chinanowno1inCO2emissionsUSAinsecondposition.

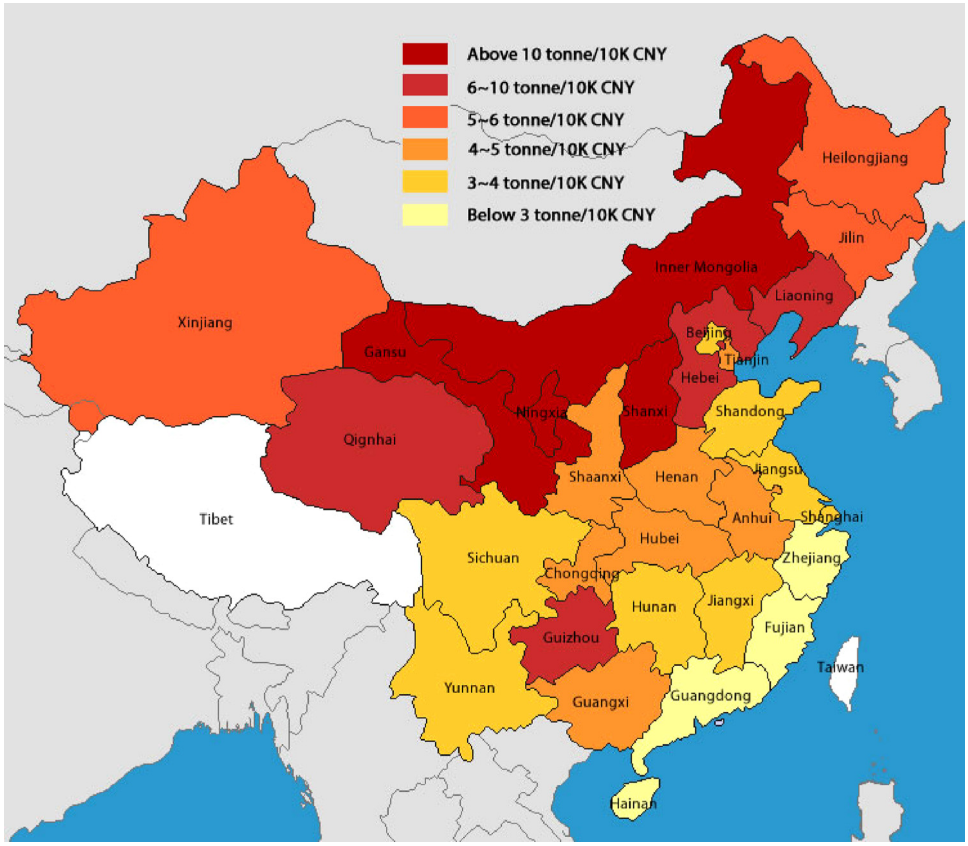

Fig. 2. Spatial distribution of average CO_2 emission intensity over the entire sample period.

monitor such a large variety of mobile and stationary sources of emissions [7]. The distinction between actual versus estimated emissions is important however, because we are not making the claim that there are spillovers in CO_2 emissions themselves, but rather there are province-level spillovers in energy consumption which in turn create CO_2 emissions. More specifically, we argue that there is spatial dependence among the drivers of energy-related emissions and other economic forces which cross province lines.

The motivation for the idea of spatial spillovers in energy consumption (which in turn creates emissions) is related to the concept of economic distance, which suggests that the closer two regions are to one another in geographic distance, the more likely their economy's will have an affect one another [8]. We analyze this spatial dependence by specifying novel spatial panel data models which control for spatial effects across space and time. That is, we estimate a model of CO_2 emission intensity based upon per-capita GDP, energy prices, population density, the structure of energy consumption, and the transportation structure at the province level from 1991–2010. We find statistically significant, spatial autocorrelation (dependence) among these driving forces and CO_2 emission intensities at the province-level in China. This spatial autocorrelation implies that any policies implemented in one province will have spillover effects in neighboring province. The determination of such spillovers is important for understanding the direct and indirect effects of province-level policies adopted in China.

This study offers four unique contributions to the literature: (1) by more explicitly considering and testing for the types of spatial dependence within the relationship between energy-related emissions and economic forces; (2) using recently developed, spatial panel data models and diagnostics to determine the most appropriate spatial econometric model; (3) offering a more rigorous interpretation of both the direct and indirect spatial impacts (spillovers); and, (4) extending the data to consider the years 1991–2010, which is important for capturing recent developments in province-level energy consumption and economic growth.

The rest of this manuscript is structured as follows. Section 2 offers the literature review. Section three offers a description of the data and the empirical framework. Section four discusses estimation results. Finally, section five concludes this study and offers suggestions for future research.

2. Literature review

The carbon dioxide emissions is generally defined as a linear function of fossil fuel combustion and cement manufacturing. The amount of carbon dioxide emissions is determined by the use of fossil fuels as a feedstock and the chemical composition of the fuel source. That is, each of fossil fuels is weighted by its corresponding conversion ratio, which is determined by the chemical properties of the fuel. In turn, the sum of the weighted total fuel consumption yields an estimate of CO_2 emissions [9]. This estimate of CO_2 emissions, based on energy consumption, is frequently used as proxy for actual emissions (e.g., it is used by the World Bank's World Development Indicators and the Carbon Dioxide Information Analysis Center within the U.S. Department of Energy) since carbon dioxide emissions are highly related to energy consumption [10]. Therefore, factors that influence CO_2 emission intensity also influence energy intensity.

Past studies have found that the main factors driving China's environmental emissions are pressures from population, urbanization, industrialization, GDP per capita and energy intensity [11–16]. These factors have a positive effect on emissions but the impact has

been gradually declining over the past few decades [15]. Using a decomposition analysis (similar to the Kaya identity), Fan et al. [12] found that GDP, energy use, and population have the greatest impact on CO_2 emissions in China from 1975–2000. Using a bounds testing procedure of cointegration, Halicioglu [17] found that carbon dioxide emissions are determined by energy consumption, income and foreign trade in the long-run relationship. Other factors such as technological advancement have also been identified as influencing China's CO_2 emissions [16].

Despite China's high (aggregate) carbon dioxide emissions, the country has experienced an overall decrease in energy intensity since the 1980s due to adjustments in the industrial sector [11]. Ma and stern [14] found that structural changes at the industrial and sectoral level are the main factors driving the decline of China's overall energy intensity for the period 1980–2003. In addition to structural changes, Hang and Tu [13] found that energy prices have played an important role in the improvement of China's energy efficiency, which in turn has put less pressure on the country's energy intensity.

A possible shortcoming of previous studies within this literature is that all assume that inter-jurisdiction regions to be cross-sectionally independent and the spatial interaction effects are ignored. Anselin [18] and LeSage and Pace [19] point out that a local region's characteristics may depend on its neighbors; therefore, ignoring spatial dependence would lead to model misspecification or create biased estimated parameters in an ordinary least squares framework.

The importance of geography is captured in the argument for a "pollution displacement" hypothesis in which higher-income regions are effectively exporting their pollution to lower-income regions; or, one could argue that higher-income regions are inducing greater emissions by importing goods from the more energy intensive, lower-income regions. The pollution haven hypothesis has been explored in context of the environmental Kuznets curve [20,21]. If this hypothesis is correct, the carbon dioxide emissions of one poor region neighboring a rich region would more likely have higher emissions since distance and the existence of common land borders are important factors in facilitating trade. Geography has been identified as a major determinant of cross-country economic growth due to factors such as the diffusion of technology [22]. One could argue that CO_2 emission intensity would decrease with technological improvements, so the diffusion of technology could possibly help improve neighboring environmental conditions. Geography is also important because environmental policies promulgated in one region might spill over into other neighboring regions [23]. Local governments, such as a province, likely assess policy against those of their neighbors in order to reduce the costs of decision making. Hence, spatial interaction effects should be considered in the context of regression modeling.

Recognizing the importance of geography, Auffhammer and Carson [24] use a spatial econometrics model to forecast China's emissions using province-level information. Yu [25] incorporated spatial dependence into a statistical model of China to analyze the influential factors of China's regional energy intensity. The authors found that incorporating spatial dependence into their regression model, in general, improved forecasts and the analysis. Despite their contribution, the authors only estimated the spatial dependence within the dependent variable and the error term in the regression model. They did not explore different data generating processes for the spatial dependence (for example, a spatial Durbin model is specified with a spatially lagged dependent variable and with spatial autocorrelation among the explanatory variables) nor did they offer a rigorous interpretation of the spatial impacts, which include the direct and indirect effects estimation of the independent variables. These small deficiencies, therefore present a gap in the literature.

3. Data and empirical approach

3.1. *Data*[4]

3.1.1. *Dependent variable*

This paper uses the carbon dioxide emission intensities as the dependent variable, which include a panel of China's 30 provinces and municipalities for the period 1991–2010 (Hong Kong, Macao, Taiwan and Tibet are not included due to lack of data). The emission intensities are calculated as the units of CO_2 emissions per unit GDP (CO_2 emissions divided by GDP). We estimate the CO_2 emissions for each province by following the revised 1996 Intergovernmental Panel on Climate Change's "Guidelines for National Greenhouse Gas Inventories" [26]. The Carbon Dioxide Information Analysis Center, within the U.S. Department of Energy (DOE), defines carbon dioxide emissions as a linear function of fossil fuel combustion and cement manufacturing.[5] More specifically, emissions are estimated by multiplying the amount of fuel usage by a thermal conversion factor as determined by the chemical properties of the fuel. Itkonen [9] offers a simple explanation of how the energy emissions are estimated.

$$CO_{2,t} \equiv \alpha_{oil}E_t^{oil} + \alpha_{coal}E_t^{coal} + \alpha_{gas}E_t^{gas} + \alpha_{flare}E_t^{flare} + S_t, \qquad (1)$$

where $\alpha_{oil}, \alpha_{coal}, \alpha_{gas}, \alpha_{flare} > 0$ are the related thermal conversion factors. Different organizations, such as the DOE, the institute of Energy Economics of Japan, and the Energy Research Institute of National Development and Reform commission (NDRC) of China, calculate emissions differently, but the differences are often negligible. In this study, we choose the coefficients reported by the Energy Research Institute of NDRC of China in 2003. Following the equation offered by Itkonen [9], we calculate CO_2 emissions based on the final energy consumption of three primary types of energy sources in China: coal, petroleum and natural gas [27]. We assume that all carbon in the fuel is completely combusted and transformed into carbon dioxide.

3.1.2. *Explanatory variables*

The explanatory variables include per-capita GDP, energy prices, population density, the ratio of coal consumption to total energy consumption, and the total length of highways. All of the variables are derived from the China Statistic Yearbooks and the provincial Statistical Yearbooks [28].

The specific definition of each variable is provided here:

1. Per capita GDP (PCGDP): measured by the gross domestic product divided by the population. We hypothesize that economic growth is one of the most important factors in determining energy consumption and energy efficiency, which then exerts an influence on CO_2 emission intensity. The empirical results of Markandya [29] and Qi [30] indicated that the decrease in the gap of per-capita GDP between developing and developed countries has led to the decrease of the gap in energy intensity. Yu [25] also indicated that an increase of province level per-capita GDP reduced the energy intensity in China. Further, Fan et al. [31] using a decomposition analysis, found that the largest contributor to the decline carbon intensity was a reduction in the percentage of coal in the primary energy mix. This reduction in carbon intensity in tandem with a period of economic expansion is consistent with the environmental Kuznets curve hypothesis [32].

[4] The data set for this study, in Excel format, is available for replication purposes.

[5] Due to data limitations we do not calculate CO_2 emissions from cement manufacturing.

Based on these findings, we hypothesize that per-capita GDP will reduce CO_2 emission intensity at the province-level in China.

2. Energy prices (EP): as in the standard economic law of demand, we hypothesize that energy prices are an important determinant of energy consumption. We predict that the energy price for a specific fossil fuel will be inversely related to the consumption of that fuel type; and since CO_2 is measured based upon energy consumption, we assert that energy prices will be inversely related CO_2 emission intensity. In China, the main cost of the energy consumption of each region is the cost of raw materials, fuels, and power. Purchasing price indices for raw materials, fuels and power reflect changes in the level and degree of prices paid by industrial enterprises when they purchase these production inputs, so we will use these indices to represent the energy prices of each province [33].
3. Population density (PD): is measured as the population divided by the area of each province. Theoretically, as China's population increasingly migrates to urban areas, which have greater access to modern energy technologies (e.g., automobiles, home heating and cooling). This greater energy consumption is particularly relevant to carbon dioxide emissions since 'consumption-based' rather than 'production-based' measures of carbon dioxide emissions are utilized. The empirical results of Auffhammer and Carson [24] indicated that population density is positively related to CO_2 emissions in China. So we hypothesis a positive relationship between population density and CO_2 emission intensity. However, agglomeration effects can optimize the spatial allocation of production and energy resources which could improve production and energy efficiencies.
4. Ratio of coal consumption to total energy consumption (RCC): represented as the percentage of coal consumption of the total energy consumption. Since coal consumption accounted for the highest rate of total energy consumption in China [3], and the power transfer efficiency of coal is relatively lower than petroleum, natural gas and hydro-power, we predict that the higher the ratio of coal consumption the higher the CO_2 emission intensity in each province.
5. Total length of highways (TH): is measured as the total kilometers of paved highways at the province level in a particular year. The total length of highways serves as a proxy for activity in the transportation sector. The transportation sector in China accounts for a large portion of CO_2 emission intensity. Road transportation alone is consuming about half of the total energy used by the transport sector in China. Advances in technology have led to a reduction in certain pollution emissions, such as nitrogen oxides, sulfur dioxides, and ground-level ozone, but the transportation sector is still the largest and fastest growing consumer of crude oil and the largest producer of CO_2 emissions produced from oil [34]. Thus, we expect an increase in the total length of highways will increase the CO_2 emission intensity.

3.2. Model specification

3.2.1. Regression model

We specify the regression model as follows:

$$ci_{it} = \beta_0 + \beta_1 pcgdp_{it} + \beta_2 ep_{it} + \beta_3 pd_{it} + \beta_4 rcc_{it} + \beta_5 th_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{2}$$

where all variables are defined as natural logarithms in order to interpret the coefficients as elasticities. The parameter μ_i denotes the individual effect (or heterogeneity) for each province and η_t denotes a common time effect. We treat the individual effect as fixed meaning that we assume that this variable is correlated with the explanatory variables and approximately fixed over time for each province within the sample. If we estimate (2) without controlling for the individual effect, then estimation may result in omitted variable bias if the fixed effect is correlated with the explanatory variable. The individual effect can be interpreted as characteristics within provinces that do not change over time such as unobservable geographic characteristics. The time period effects control for time-specific shocks that affects all provinces in a given period of time; e.g., national policies that affect CO_2 emissions across all provinces in China.

3.2.2. Spatial econometric models

Spatial relationships can be modeled in a variety of ways depending on the relationship between the dependent variable and the explanatory variables. Following Elhorst [35], there are three basic models that are used to estimate the spatial panel data models.

The first model is the spatial autoregressive model (SAR), which is sometimes called the spatial lag model (SLM). The SAR model hypothesizes that the value of the dependent variable observed at a particular location is partially determined by a spatially weighted average of neighboring dependent variables. That is, CO_2 emission intensity in region i is affected by the energy-related CO_2 emission intensity in region j. This model cannot be estimated by ordinary least squares (OLS) because of the problem of simultaneity of the dependent variables on the right hand side (RHS) of eq. (3). The SAR model is specified as

$$Y_{it} = \rho \sum_{j=1}^{N} W_{ij} Y_{jt} + X_{it}\beta + \mu_i + \eta_t + \varepsilon_{it}, \quad i = 1, ..., N, \ t = 1, ..., T \tag{3}$$

where Y_{it} denotes the dependent variable (CO_2 emission intensity) for the cross-sectional unit i at time t. The parameter ρ denotes the scalar spatial autoregressive parameter. X_{it} is a matrix of observations on the explanatory variables, which include per-capita GDP, energy prices, population density, ratio of coal consumption to total energy consumption, and the total length of highways. The parameter β is a column vector of regression coefficients. The error term, ε_{it}, is assumed to be independently and identically distributed with a zero mean and variance σ^2. The parameter μ_i denotes individual specific effect for each province, which control for all space-specific time-invariant variables that if omitted could potentially bias the coefficient estimates. The parameter η_t denotes a time-period specific effect.

The term $\Sigma_j W_{ij} Y_{jt}$ denotes the interaction effect of the dependent variable Y_{it} with the dependent variables Y_{jt} in neighboring provinces, where W_{ij} is the i, j^{th} element of a pre-specified nonnegative $(N \times N)$ spatial weighting matrix W. This matrix describes the arrangement of the spatial units and it is a compact reflection of the geographic relationship among different provinces. In the literature, there are a large number of weighting matrix specifications. However, two common specifications are the binary contiguity matrix and the distance function matrix. The neighboring relation in the binary contiguity matrix is determined by observing whether the regions share a common border. That is, if two regions i and j are neighbors, then the matrix elements $w_{ij}=1$ and $w_{ij}=0$ otherwise. The element in the distance function matrix is determined by the distant function $w_{ij}=f(d_{ij})$, where d_{ij} refers to the distance between the geometric centroid (or capitals) of region i and region j. For additional information about the spatial weighting matrix the reader is referred to LeSage and Pace [19].

In this study, we choose the binary contiguity matrix where the elements of the spatial weight matrix are defined as $w_{ij}=1$ if i is adjacent to j, and $w_{ij}=0$ if i is not adjacent to j. Consistent with the literature, we normalize the spatial weight matrix according to row standardization [19]. That is, the sum of elements w_{ij} in each

row equals one. Row standardization allows us to interpret spatial spillover effects as an average of all neighbors.

An alternatively way to incorporate spatial autocorrelation in a regression model is to specify a spatial process of the disturbance (error) term, which is called spatial error model (SEM). This refers to a situation in which the unobserved shock to province i is affected by unobserved shocks in neighboring regions. The SEM model is specified as

$$Y_{it} = X_{it}\beta + \mu_i + \eta_t + \phi_{it}$$
$$\phi_{it} = \lambda \sum_{j=1}^{N} W_{ij}\phi_{it} + \varepsilon_{it} \tag{4}$$

where λ denotes the spatial autocorrelation coefficient on the error term.

A third form of spatial relationship occurs when the dependent variables can be predicted as a function of spatially lagged values of the explanatory variables as well – this is called the spatial Durbin model (SDM). The SDM model is given by

$$Y_{it} = \rho \sum_{j=1}^{N} W_{ij}Y_{jt} + X_{it}\beta + \sum_{j=1}^{N} W_{ij}X_{jt}\gamma + \mu_i + \eta_t + \varepsilon_{it} \tag{5}$$

where γ is a $(K \times 1)$ vector of spatial autocorrelation coefficients on the explanatory variables and ρ denotes a scalar spatial autocorrelation coefficient on the dependent variables in this particular specification.

3.3. Estimation method

3.3.1. Global spatial autocorrelation

The global spatial autocorrelation (i.e., a general measure of spatial dependence) of China's overall (energy-related) CO_2 emission intensity can be measured by Moran's I index. The formula for calculating global Moran's I index is

$$\text{Moran's I} = \frac{\sum_i \sum_j \omega_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{S^2 \sum_i \sum_j \omega_{ij}}$$
$$S^2 = \frac{1}{n}\sum_i (Y_i - \overline{Y})$$
$$\overline{Y} = \frac{1}{n}\sum_i Y_i \tag{6}$$

where Y_i and Y_j represent CO_2 emission intensity of province i and j, respectively. The term w_{ij} denotes the element in the i^{th} row and j^{th} column of the spatial weight matrix. The global Moran's I index is defined over the interval $[-1, 1]$. Positive Moran's I values imply positive spatial autocorrelation (or spatial dependence), where a value of one indicates perfect correlation. Conversely, negative values imply negative autocorrelation, where a value of negative one indicates perfect dispersion. A zero value indicates a random spatial pattern. The significance of Global Moran's I index can be tested by standard z-statistics.

3.3.2. Spatial econometric analysis[6]

In this study, we follow the specification tests outlined in Elhorst [35]. The first step is to test the standard, non-spatial panel models against the SAR and SEM models. To test whether the spatial effects model (against the non-spatial models) offer an appropriate specification we employ a series of Lagrange Multiplier (LM) tests.

The second step is to investigate the joint significance of individual fixed effects and time-period fixed effects. Likelihood ratio (LR) tests are used to check the null hypothesis that the individual fixed effects are jointly insignificant and/or the time-period fixed effects are jointly insignificant. If the p-value is less than 5%, then we reject the null hypothesis of joint non-significance.

If we fail to reject the spatial model in the previous step, then the third step will be to test whether the SDM model can be simplified to the SAR or SEM model. The hypothesis tests for the third step are

$$H_0 : \gamma = 0 \tag{7}$$

$$H_0 : \gamma + \rho\beta = 0. \tag{8}$$

H_0: $\gamma=0$ examines whether the spatial Durbin model can be simplified to the spatial lag model, and H_0: $\gamma+\rho\beta=0$ examines whether it can be simplified to the spatial error model [35]. Both tests follow a chi-squared distribution. A rejection of both hypotheses suggests that the spatial Durbin model provides the best fit to the data. Conversely, a failure to reject the first hypothesis suggests that the spatial lag model best describes the data. A failure to reject (7) can be balanced against the results of the (robust) LM tests for the spatial autoregressive model. Similarly, a failure to reject the second hypothesis (8) suggests that the spatial error model best describes the data – which can also be balanced against the results of the (robust) LM tests for the spatial error model.

The last step is to estimate the spatial spillover effects of CO_2 emission intensity. We follow LeSage and Pace [19] by estimating the direct and indirect effects of the explanatory variables. Direct effects estimates measure the impact of changing an independent variable on the dependent variable of a spatial unit. Loosely speaking, the indirect effects estimates measure the impact of changing an independent variable in a particular unit on the dependent variable of all other units.

4. Estimation results

4.1. Global spatial autocorrelation

Table 1 displays China's Global Moran's I index of carbon dioxide emission intensity and its significance in various periods from 1991 to 2010. The overall Moran's I over twenty year period is 0.394, which indicates positive spatial correlation at the 1% significant level. In each period, the test reveals that CO_2 emission intensity displays positive spatial autocorrelation at a 5% significant level. Recall, the CO_2 emissions are estimated based upon energy consumption, so positive spatial autocorrelation in this sense is referring to the spatial dependence of energy consumption. This indicates that China's carbon dioxide emission intensity tend to cluster together. Specially, we find that provinces with high carbon dioxide emission intensities have a tendency to cluster together, whereas the provinces with low carbon dioxide emission intensities cluster together.

Despite our findings of the spatial autocorrelation of carbon dioxide emission intensity, the Moran's I test only assesses the overall pattern and trend, and Moran's I is only effective when the spatial pattern is consistent across the provinces. If some of the provinces have positive spatial autocorrelation while others have negative spatial autocorrelation, then the effects could offset one other. In which case, the global Moran's I test may reveal non-spatial autocorrelation characteristics.

To further examine the clustering of among provinces, we employ a Moran's I scatter plot displayed in Fig. 3. In this scatter plot, the horizontal axis refers to the deviation of provincial average carbon dioxide emission intensity from 1991 to 2010, whereas the vertical axis refers to the spatial lags of the deviation of the average carbon dioxide emission intensity. We calculate the spatial lags by using a first-order contiguity spatial weight matrix, which produces an average measure

[6] The regressions were conducted using Matlab code provided by James LeSages and Paul Elhorst. Matlab is a commercially developed numerical computing environment and programming language. For additional information about Matlab, the reader is referred to the developer's website: http://www.mathworks.com/products/matlab.

Table 1
Moran's I index of China's CO_2 emission intensity.

	1991–2010	1990–1995	1996–2000	2001–2005	2006–2010
Moran's I	0.394	0.450	0.389	0.274	0.205
Z-statistic	3.650	4.129	3.607	2.630	2.034
p-Value	0.000	0.000	0.000	0.008	0.042
Significant level	***	***	***	***	**

Note: The symbol * denotes a significance level of 10%.
** 5% significance level.
*** 1% significance level.

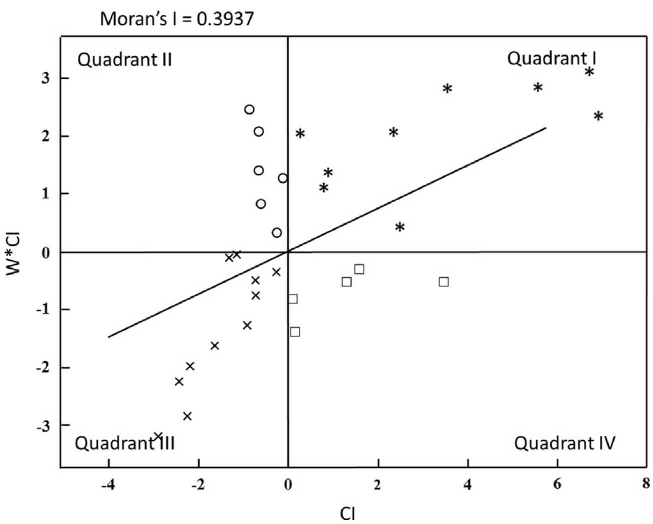

Fig. 3. Moran scatter plot of China's provincial CO_2 emission intensity (1991–2010).

of carbon dioxide emission intensity among neighboring provinces. The four quadrants in the scatter plot depict the following:

1. HH clustering (quadrant I) – provinces with high CO_2 emission intensity are associated with neighboring province with high CO_2 emission intensity (the star points).
2. LH clustering (quadrant II) – provinces with low CO_2 emission intensity are associated with neighboring provinces with high CO_2 emission intensity (the circle points).
3. LL clustering (quadrant III) – provinces with low CO_2 emission intensity are associated with neighboring provinces with low CO_2 emission intensity (the cross points).
4. HL clustering (quadrant IV) – provinces with high CO_2 emission intensity are associated with neighboring provinces with low CO2 emission intensity (the square points).

The results in Fig. 3 consist of the following:

1. Nine provinces in quadrant I: Heilongjiang, Liaoning, Inner Mongolia, Hebei, Shanxi, Shaanxi, Ningxia, Gansu, and Xinjiang.
2. Six provinces in quadrant II: Beijing, Tianjin, Henan, Shandong, Sichuan, and Chongqing.
3. Ten provinces in quadrant III: Shanghai, Jiangsu, Zhejiang, Hubei, Hunan, Jiangxi, Fujian, Guangdong, Hainan, and Yunnan.
4. Five provinces in quadrant IV: Qinghai, Anhui, Guizhou, Guangxi and Jilin.

During this period of analysis, 63.33% (19 provinces) show similar characteristics of spatial autocorrelation. Further, 30% (nine provinces) in quadrant I and 33.33% (10 provinces) in quadrant III demonstrate similar characteristics of positive spatial autocorrelation. On the other side, 20% (six provinces) in quadrant II and 16.67% (five provinces) in quadrant IV demonstrate negative spatial autocorrelation. This means that the spatial autocorrelation and dispersion of provincial CO_2 emission intensity exist at the same time.

The Moran's I analysis implies that China has significant clustering of emissions in high emitting provinces and significant clustering of emissions in low emitting provinces for the period of observation. The statistically significant, spatial autocorrelation among provinces implies that standard ordinary least squares regressions of the drivers of emissions may lead to estimation bias in the regression results. Therefore, we test whether a spatial panel data model is preferable to non-spatial models in the analysis of the drivers of emissions at the province-level in China.

4.2. *Empirical results of spatial econometric models*

The estimation results for the non-spatial panel data models are reported in Table 2. Columns (1) through (4) represent the estimation results of pooled OLS, individual fixed effects only, time-period fixed effects only, and individual and time-period fixed effects, respectively. When using the classical LM tests, both the hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially autocorrelated error term are strongly rejected at a 1% significance level with the exception of including both the individual and time-period fixed effects. When using the robust LM tests, the hypothesis of no spatially lagged dependent variable is still rejected at a 1% significance level for each of the specifications. The hypothesis of no spatial autocorrelated error term is rejected at 1% significance level when individual fixed effects are included and 5% significance level when the time-period fixed effects are included. But this same hypothesis (robust LM spatial error) cannot be rejected for the pooled OLS. These results seem to imply that the SAR model is a more appropriate specification than the non-spatial model as we find fairly consistent evidence across all models to reject the null hypothesis of no spatial lag. We find mixed results to reject the hypothesis for spatially autocorrelated error term.

To investigate the joint significance of the individual fixed effects and time-period fixed effects, we perform the LR tests. The null hypothesis that the individual fixed effects are jointly insignificant is rejected at a 1% level (620.9317, with 30 degrees of freedom, $p<0.01$), and the null hypothesis that the time-period fixed effects are jointly insignificant is also rejected at a 1% level (71.7303, with 20 degrees of freedom, $p<0.01$). These test results seem to justify the extension of the model with the two-way fixed effects model i.e., include both the individual fixed effects and time-period fixed effects. We also conduct a Hausman test to further test the correct panel data specification between a fixed effects and random effects model. The Hausman test results (44.6832, with 11 degrees of freedom, $p<0.01$) imply that the fixed effects model is the more appropriate specification. Table 3 gives the estimation results of CO_2 emission intensity according to the three spatial specification panel data models (as per the LR test results we include both the individual and time-period fixed effects).

Table 2
Estimation results of non-spatial panel data models.

Determinants	Pooled OLS	Individual fixed effects	Time-period fixed effects	Individual and time-period fixed effects
pcgdp	−0.413***	−0.642***	−0.366***	−0.755***
	(−23.038)	(−21.822)	(−10.382)	(−7.466)
ep	0.476**	0.427***	−0.255	0.199
	(2.574)	(3.737)	(−0.743)	(0.896)
pd	−0.180***	−1.007***	−0.193***	−1.153***
	(−13.119)	(−5.328)	(−14.163)	(−5.610)
rcc	1.036***	0.149	1.061***	0.080
	(16.188)	(1.441)	(17.068)	(0.806)
th	−0.226***	0.207***	−0.228***	0.056
	(−12.414)	(5.032)	(−10.362)	(1.035)
Intercept	5.683***	NA	NA	NA
	(6.229)			
σ^2	0.137	0.049	0.123	0.044
R^2	0.723	0.900	0.751	0.912
Log like	−251.420	55.585	−219.016	91.450
Sample	600	600	600	600
LM spatial lag	94.862***	60.1405***	26.821***	0.876
Robust LM spatial lag	57.297***	71.2093***	32.183***	7.692***
LM spatial error	37.572***	15.2978***	5.624**	0.062
Robust LM spatial error	0.007	26.3666***	10.986***	6.878***

Note: All variables are measured as natural logs. Numbers in the parentheses represent *t*-stat values.
The symbol * denotes a significance level of 10%.
** 5% significance level.
*** 1% significance level.

Table 3
Estimation results of spatial panel data models and interaction effects.

Determinants	SAR	SEM	SDM
pcgdp	−0.640***	−0.749***	−0.519***
	(−6.300)	(−7.118)	(−5.073)
ep	0.142	0.204	0.106
	(0.639)	(0.888)	(0.491)
pd	−1.146***	−1.165***	−1.282***
	(−5.550)	(−5.440)	(-5.941)
rcc	0.124	0.083	0.257***
	(1.243)	(0.809)	(2.624)
th	0.073	0.054	0.150***
	(1.341)	(0.962)	(2.748)
ρ	0.342***	NA	0.106**
	(7.175)		(1.950)
λ	NA	0.094*	NA
		(1.658)	
*W**pcgdp	NA	NA	−0.702***
			(−8.247)
*W**ep	NA	NA	0.203
			(0.552)
*W**pd	NA	NA	1.062***
			(2.656)
*W**rcc	NA	NA	−0.343*
			(−1.802)
*W**th	NA	NA	0.275**
			(2.362)
σ^2	0.044	0.047	0.039
R^2	0.918	0.912	0.927
Sample	600	600	600
Log like	84.973	91.496	147.949

Note: All variables are measured as natural logs. Numbers in the parentheses represent *t*-stat values.
* 10% significance level.
** 5% significance level.
*** 1% significance level.

Since the Lagrange Multiplier test results suggest that the spatial models are a more appropriate specification than the non-spatial models, we will continue to test which spatial model offers the best fit for the data. We perform both the Wald test and LR test to test the hypothesis whether the SDM model could be simplified to the SAR model or SEM model. According to the Wald test result (105.233, with 5 degree freedom, $p < 0.01$) and LR test result (125.952, with 5 degree freedom, $p < 0.01$), the null hypothesis (7) that the SDM model can be simplified to the SAR model is rejected at a 1% significance level. Similarly, the null hypothesis (8) that the SDM model can be simplified to a SEM model is also rejected at a 1% significance level based on the Wald test result (117.640, with 5 degree freedom, $p < 0.01$) and LR test result (112.906, with 5 degree freedom, $p < 0.01$). These results imply that both the spatial lag model and spatial error model are rejected in favor of the spatial Durbin model. Therefore, we conduct a sensitivity analysis of the SDM model.

As can be gleaned from the estimated results in Table 3, the coefficients of independent variables are basically consistent with the theoretical expectations offered in Section 3.1.2. Just focusing on the SDM coefficient estimates, an interpretation of the coefficient on per-capita GDP is that a 10% increase of per-capita GDP is associated with 5.19% decrease of the CO_2 emission intensity (holding all else constant). An interpretation of the ratio of coal consumption to total energy consumption is that a 10% decrease will lead to a 2.57% decrease in emission intensity. Similarly, the total length of highways coefficient implies that a 10% increase will lead to 1.5% increase of CO_2 emission intensity. These results imply that an improvement in the economic performance at the province level will lead to a decrease of CO_2 emission intensity (as reflected in the coefficient on per-capita GDP); while increasing the ratio of coal consumption to total energy consumption and the total length of highways will lead to the increase of the CO_2 emission intensity. The coefficient on the ratio of coal to total energy consumption implies that replacing coal consumption with non-coal energy consumption is an effective mechanism to decrease CO_2 emission intensity. Further, the coefficient on the total length of highways suggests that technological advancements in energy efficiency (i.e., barring any rebound effects) of the transportation sector may play a role in decreasing CO_2 emission intensity.

The results for the SDM in Table 3 also suggest that a 10% increase in population density is associated with a 12.82% decrease

Table 4
Direct and indirect effects of SDM model.

Determinants	Direct effect	Indirect effect	Total effect
pcgdp	−0.533***	−0.827***	−1.360***
	(−5.412)	(−7.594)	(−9.626)
ep	0.105	0.231	0.336
	(0.466)	(0.536)	(0.697)
pd	−1.252***	1.002**	−0.250
	(−5.738)	(2.278)	(−0.581)
rcc	0.247**	−0.353	−0.106
	(2.410)	(−1.728)	(−0.461)
th	0.157***	0.310**	0.467***
	(2.934)	(2.457)	(3.463)

Note: All variables are measured as natural logs. Numbers in the parentheses represent *t*-stat values.
The symbol * denotes a significance level of 10%.
** 5% significance level.
*** 1% significance level.

of the CO_2 emission intensity, which implies that agglomeration effects are leading to an improvement in energy efficiency which in turn reduces emission intensity. Contrary to expectations, we do not find a significant relationship between energy prices and CO_2 emission intensity, which implies that energy prices do not play a role in reducing CO_2 emission intensity. A possible explanation for this lack of statistical significance is that the Chinese government subsidizes energy prices thereby keeping prices artificially below the market price.

Given the statistically significant spatial autocorrelation coefficient, ρ, the parameter estimates in the two-way fixed effects spatial Durbin model cannot be interpreted as marginal effects as in the case of non-spatial models. Therefore, following LeSage and Pace [19], we estimate the direct and indirect effects to yield an interpretation of the spatial spillover effects. The direct and indirect effects of each explanatory variable are reported in Table 4. The difference between the direct effects (Table 4) and the coefficient estimates (Table 3) are due to the feedback effects that arise as a result of impacts passing through neighboring provinces and back to the provinces themselves. The feedback effects include both the impacts from the spatially lagged dependent variable ($\rho\sum W_{ij}Y_{jt}$) and the impacts from the spatially lagged value of the explanatory variable itself ($\sum W_{ij}X_{jt}\gamma$).

The results in Table 4 reveal that the direct effects of all the explanatory variables (with the exception of energy prices) are statistically significant. Among the direct effects, per-capita GDP, population density, and the length of highways are significant at 1% level. The direct effect of the ratio of coal to total energy consumption is significant at the 5% level.

In the non-spatial model, the indirect effects are set, by construction, to zero; however, based on the *t*-statistics calculated from a set of 1000 simulated parameter values [19] in the two-way fixed effects spatial Durbin model, there are three statistically significant indirect effects. The indirect effect of per-capita GDP is significant at the 1% level, and the indirect coefficients on population density and length of highways are significant at a 5% level. These coefficients imply that a change per-capita GDP, population density, and length of highways in one particular province has an average cumulative effect on the corresponding variables in neighboring provinces.

The statistically significant coefficients on both the direct effect and indirect effect of per-capita GDP are negative which implies that the own-province per-capita GDP increases will reduce the CO_2 emission intensity of both own province and neighboring provinces. The coefficients of both the direct effect and indirect effect of total length of highways are positive and significant, and the implication is that an increase in own-province highway construction leads to an increase of both own province and neighboring province CO_2 emission intensity. The negative coefficient on the direct effect and positive coefficient on the indirect effect of population density imply that own-province population density increases will decrease own CO_2 emission intensity but increase the emission intensity of neighboring provinces.

5. Conclusions

In this paper, we analyzed the influence of economic activity, energy prices, population density, energy consumption structure, and the transportation structure on CO_2 emission intensity in China. We used spatial econometrics methods so as to avoid the potential coefficient bias from ignoring spatial autocorrelation as in ordinary least squares estimation.

Our regression results suggest that per-capita GDP reduces CO_2 emission intensity, which implies that promoting the local economic development, may help to reduce CO_2 emission intensity. These results suggest that economic development can still be compatible with CO_2 emission mitigation as China is in the middle stages of industrialization. A possible policy prescription for China would be to target a rate of increase per-capita GDP but weigh such targets with policies to reduce emission intensities.

Our findings suggest that an increase in population density leads to a decrease of CO_2 emission intensity. The provinces with large population density, such as Shanghai, Beijing and Tianjin, have relative low CO_2 emission intensity; and the provinces with small population density, such as Xinjiang, Ningxia and Inner Mongolia, have relatively high CO_2 emission intensity. This finding suggests that population concentration could improve the production efficiency and energy efficiency so as to decrease emission intensities. This does not imply, however, that population control should be unmitigated. This study also finds that an increase in the ratio of coal consumption to total energy consumption leads to a significant increase in CO_2 emission intensity. Compared with the other energy resources, the power transfer efficiency of coal is relatively low. This finding may suggest that the Chinese government should encourage the development of less carbon-intensive energy resources such as natural gas or renewables.

Our regression results also suggest that an increase in the total length of highways leads to an increase of CO_2 emission intensity. This finding suggests that the Chinese government should continue to encourage technological advancements which reduce emission intensity and encourage further fuel efficiency standards in its transportation sector, especially as China's transportation infrastructures continues to grow at an accelerated pace.

Moreover, we find that the energy prices in China have no significant effect on the CO_2 emission intensity, which differed from our expectations. A possible explanation for this is that government policies such as subsidies and price controls have artificially lowered energy prices in order to stimulate economic growth. China has recently instituted market-oriented reforms so that the price of fossil fuels more accurately reflects the true market cost [13]. This finding may suggest that the Chinese government should further deregulate energy prices to reduce artificial price distortions.

We also find that per-capita GDP, population density, and total length of highways have a significant effect on both the own province and the neighboring province elasticities. Both of these findings are consistent with the hypothesis of economic distance [8]. These findings suggest that the Chinese government should promote the sharing and exchange of information and technology across provinces, and develop appropriate policies to strengthen cross-province development.

Our findings have implications for inter- and intra-regional land use planning and economic policy. Land use regulations can

delay residential development and increase development costs, but such regulations can address market failures (e.g., addressing the social costs of global climate change) and ensure a well-organized urban spatial structure [36]. The regression results from our spatial model imply that the driving forces of CO_2 emissions are inter-related at the province-level in China. This inter-relatedness suggests that China's province-level governments (and municipal governments) should offer coordinated land use planning and economic policy. Raising barriers to development can assist in labor relocation and possibly social mobility as increasing numbers move from rural areas to the heavily urbanized parts of the country. As the population in general becomes more affluent and educated, the populace can begin to apply pressure on the government to reduce CO_2 emissions and other harmful pollutants that have plagued the country over the past couple of decades.

This study suffers from some limitations including the problem of measurement error. Our measure of carbon dioxide emissions, which is consistent with the rest of literature, is based upon the consumption of energy, so it is subject to mismeasurement. An additional problem is that we specified a single equation, reduced-form model, not a structural model. Although these reduced-form models are used fairly frequently in the energy literature, they can offer limited information for policy decisions because such models ignore issues such as inter-fuel substitution, technical change, and changes in supply [37].

Finally, we acknowledge that spatial econometric models may suffer from issues of identification (endogeneities within the explanatory variables) and a lack of theoretical foundation as pointed out by Partridge et al. [38]. But the same issues can be pointed out about reduced-form models in the econometrics literature in general. The relationship between CO_2 emissions and economic drivers is highly complicated, so studies often use decomposition analyses (with similar explanatory variables as this particular study) such as the Kaya identity found within IPCC reports [26]. Decomposition analyses are useful for analyzing this relationship for descriptive purposes, but it is merely an accounting identity not a rigorously defined statistical analysis. Therefore, we argue that spatial econometric models will continue to contribute to this larger literature as it helps to disentangle the complicated relationship between emissions and the economy.

Further research may consider testing the “out-of-sample” forecast performance of the spatial econometric versus standard econometric models. Spatial econometric models are often shown to outperform standard econometric models “within sample,” so it would be interesting as an alternative validation strategy to see how the spatial econometric models perform against empirical reality. This additional step would have added considerable more complexity to our current analysis, so we leave this exercise for future research.

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